

Article

Adoption of Google Meet by Postgraduate Students: The Role of Task Technology Fit and the TAM Model

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Abstract: The use of online meeting programs, such as Google Meet (GM), provides several benefits for teachers and students in terms of achieving learning goals outside of the classroom. Depending on the requirements and goals of the students, a variety of apps might be employed. The point of the study was to address a vacuum in the knowledge with regard to the acceptability of online meeting apps, such as GM and their role. Effectiveness in terms of utilizing GM and attitudes towards using GM are two factors that impact learners' use of this app for educational purposes. While researchers have examined google meet application acceptance in a variety of contexts, perceived ease of use, perceived usefulness, effectiveness to utilize google meet and attitude towards using Google Meet as a mediating variable in measuring education has not been explored using the technology acceptance model (TAM). As a result, the study's purpose was to create a new paradigm by merging TAM with external elements including subjective norms, task-technology fit, and quality of information. This study involved a total of 208 postgraduate students at College of Education at King Saud University. Students were polled using the structural equation modeling (SEM) approach to determine their approximate expectations with regard to online meeting adoption. According to the findings, subjective norms, perceived enjoyment, task-technology fit, and quality of information have a positive impact on perceived usefulness and perceived ease of use, which in turn has a positive impact on perceived usefulness and perceived ease of use, which finally leads to a positive effect on effectiveness to utilize GM and attitude towards using Google Meet towards adoption of GM during COVID-19. As a result, higher education institutions should promote the usage of online meeting tools, such as GM, as part of learning processes as a long-term strategy.

Keywords: Google Meet; technology fit and technology adoption; structural equation modeling (SEM)



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1. Introduction

During the lockdown in the world, there was a switch from the traditional face-to-face teaching and learning to online learning, designed to assist in lesson delivery through synchronous platforms such as Google Meet, Zoom and other online learning platforms [1–3]. Although it is claimed that using online learning and teaching has accomplished much in recent years, it should have become a must-use in most educational facilities in recent times, especially in higher education [4]. These accomplishments may be dependent on the level of perceived ease of use, usefulness, as well as intention to use GM to enable online learning. Even though most of the attention in Saudi Arabia has shifted to online learning platforms, many institutions remain severely underfunded [3,5]. As a result, learning has still not been developed using these learning platforms, since institutions may lack the necessary internet connectivity [6–8]. According to the literature, efficiency in terms of online teaching and effective learning is often correlated with the degree of setup of online course space using such technologies and resources effectively, such as Padlet, Zoom implementation, GM, and many others in an effective and efficient manner [9–11]. Although research studies have

been able to analyze the immense contributions of social media platforms, online media, and tools related to online learning, it may appear that the varying forms of their success in terms of efficacy, effectiveness, efficiency, and satisfaction derived by users are too general to apply in emergency situations such as the COVID-19 pandemic outbreak, as this study points out [12,13]. Google Meet has been widely documented in previous and current studies as having made a significant contribution to teaching and learning, causing many academics to view it as successful and efficient for online learning use [12–14]. However, it is sufficient to remark that little is known about users' perceptions of Google Meet's ease of use and utility as a learning tool for online learning. According to research, teachers believe that the use of online platforms/resources such as Instagram, GM, and many others has allowed learners to encounter ideal learning implementation relating to GM when studying [15–17]. However, to the best of our knowledge, no previous research has looked into the usability perspectives of both teachers and learners in terms of perceived ease of use, utility, mindset toward the use of GM, as well as behavioral inferences. According to the above premise, attitudes toward using GM, as well as its efficacy, may influence the adoption of technology in education, especially at a time when most school systems, colleges, and academic institutions have begun to use online teaching to mitigate the hazardous and nefarious effects of coronavirus. Most universities and colleges, however, have encountered challenges in terms of teacher knowledge and technology deployment, student understanding and competency, and the difficulty of transferring teaching to virtual classrooms [18–20]. GM is now accessible on Google Play and the Apple App Store for all users. The App Store is where you can get the app and have it automatically updated. The App Store's free policy has had a favorable impact on the number of users [2,21,22]. Organizations have displayed a high level of anxiety during the spread of COVID-19 [23], given that colleges and universities need to account for two essential concerns at the same time: picking an effective e-learning instrument and ensuring the quality of information with regard to teaching and learning. As a result, the current study looks at the relevance of selecting an effective and appropriate technology that reduces fear during the instructional process. As a result, the task technology fit (TTF) factor and information quality (IQ) factor were added as external features to the TAM model to account for GM technology adoption. In addition to the novelty of both the coronavirus situation and the use of GM app, the current study is unusual in that the task technology fit (TTF) factor and information quality factor were included as external factors relating to the well established TAM model. The Google Meet app is a recent piece of software, and no studies on its influence on higher education have been conducted. Previous study has revealed a lack of understanding of the relevance of task technology fit and quality of information, which may restrict the usage of technology in educational settings.

1.1. Problem Background

The quick shift to distance learning is a challenge that all Saudi Arabian university professors, as well as those throughout the world, are currently dealing with. The Saudi Arabian Ministry of Education ordered all schools, colleges, and institutions in the nation to completely suspend student face-to-face learning beginning 8 March 2020, and instead use online learning [24]. Consequently, digital classrooms were used to replace traditional classrooms. According to [24], this research explores the students' perceptions on online learning through asynchronous learning management systems (LMS) and via synchronous video conferencing technologies such as Google Meet, Microsoft Teams, or Zoom, among others. Universities around the country have invested a significant amount of money in developing a range of online training sessions and offering basic instructions to assist academics in becoming ready to teach online [25,26]. All of this started after seven weeks of training in the second term, with a minimum of eight weeks remaining. To deal with this rapid shift in teaching technique, program managers in all Saudi Arabian universities conducted emergency seminars, as ordered by the Education Minister and University Presidents [25,26]. Several studies have shown the value of GM in higher education, as

well as its drawbacks. Online learning is convenient in terms of date and place, as well as being cost-effective [25,27,28]. The absence of direct contact, engagement, and immediate response, on the other hand, remain a significant drawback. Furthermore, not all fields, such as health science courses that need hands-on practical knowledge, can effectively employ online learning [29]. Several researchers have examined the differences between online learning and traditional face-to-face methods. How e-learning compares to traditional full-time learning with the same content determines the efficacy of e-learning [30–32]. Furthermore, several researchers have investigated using online learning as a tool in undergraduate medical education [33]. As a result, GM could be a platform that can help the learning situation become more student-centered, inventive, and adaptable in terms of teaching and learning. The usefulness of online learning and learner satisfaction, on the other hand, have been repeatedly investigated. Several researchers [2,17,34] have found that online learning is largely as good as traditional approaches. Bearing these restrictions in mind, the present study's goal is to make higher learning aware of the types of technology can fit in the best, when information quality are important factors in instructors' and students' university education. For the first time, both instructors and students are using this innovative tool to boost learning results. Because of the pandemic, higher education institutions were under pressure to create a secure teaching environment, with the internet as the primary facilitator. Choosing the finest GM platform with the most effective pedagogies, on the other hand, has proven to be a difficult task. As a result, this research aims to pave the way for the innovative element of task technology fit to ensure system quality for education within a given technology, GM. This will involve determining the groundbreaking effect of task technology fit and information quality in a specific educational setting. The TAM model was used in this study, given that it has been shown to be regularly used in technology adoption research and has proved to be an important and successful tool in previous studies [35]. Its efficacy has been well established as a result of recent investigations [9,36,37]. The purpose of this work is to create a modified version of the model and incorporate an external component that will assist answering the research questions and testing the hypotheses. The inclusion of the subjective norm, self-efficacy, perceived pleasure, task technology fit, information quality, perceived utility, ease of use, and attitude towards using GM, and determining its effectiveness, distinguishes our model from past research and adds to the paper's uniqueness.

1.2. Google Meet Used in Education

Many developing nations, such as Saudi Arabia [14], have insufficient access to formal learning management systems (LMS) for online learning and academic interaction, which is a bit different in the Middle East [14]. Many institutions were compelled to use free communication technologies such as Zoom, Microsoft Teams, and Google Classroom, as well as social media sites such as WhatsApp, Facebook, and YouTube to find alternatives [38,39]. Faculty and students from nine educational institutes in Saudi Arabia were polled, and in-depth interviews were performed as part of the study. According to the findings, proper use of such platforms might usher in a new era of social e-learning, and social media can be effectively used to create a pleasant learning environment. Qassim University's College of Medicine and Medical Sciences conducted a quantitative study on the effectiveness of live online streaming learning sessions using such apps as GM and Zoom Meet [3,37]. Using these systems, most teachers have struggled to engage students personally while both analyzing and grading the participants with honesty. In addition to the disadvantage of not covering the entire curriculum, this research [37] found that there was a lack of attendance in practice sessions. Al Faisal University in Riyadh supported a similar study [40]. According to the study, GM is a Google web service with a simple setup; it is thought that with the latest change from Google Talk to GM, it compares well to Skype and Zoom, and is recognized as one of the finest choices for group conferencing [9,41]. In fact, review articles show that there are millions of GM users, including learners and lecturers, who are already familiar with its capabilities [10,42], so there is no need to provide extensive instructional

videos on how to set it up, as there might be in the case of Zoom, Microsoft Teams, and other tools [43,44]. GM allows the user to choose their relationships in order to guarantee privacy, especially when it comes to the type and amount of information shared among students [45]. Earlier and new ideas propose that the capacity to apply real-time learning would eliminate learning gaps, promote social interaction, and remove social distances between students [46,47]. While it has been stated explicitly in this research that useful planning is critical for learners and faculty members in order to achieve scholastic goals in education [9,48], it is possible that thorough planning is required when using GM as a dialectical tool for teaching and learning. Since the usefulness or efficiency of GM is dependent on both the instructors and the learners, it will necessitate interaction between students and instructors when it comes to designing class schedules that are suitable for all [42].

2. Theoretical and Empirical Models

As a result, perceived usefulness (PU) and perceived ease of use (PEOU) should be investigated as a method for identifying an individual's preference for evaluating technology as a worthwhile tool and the likelihood of them accepting or adopting it. Attitude toward using Google Meet (ATGM) and Effectiveness (EF) correspond to a person's perception of how easy it is to use technology and how accessible they find it [49]. According to the previous premise, when people believe technology to be simple to use, they are more likely to have a good view of it; hence, the users' opinions of its utility are obvious. Similarly, when people believe technology to be beneficial, they are more inclined to embrace it. One of the fixed goals that the TAM model prefers to measure is the validation of an external influence on personal belief. As a result, it is the most powerful paradigm for explaining how people adopt technology, particularly in educational institutions [49,50]. TAM includes perceived utility, perceived enjoyment, perceived ease of use, subjective norms, self-efficacy, task technology fit, information quality, attitude toward GM, and effectiveness with regard to using GM as the common dominating aspect that may quantify two distinct perspectives. This information may have a direct impact on the adoption of GM on the part of users. All elements of TAM (perceived usefulness, perceived enjoyment, perceived ease of use, subjective norms, self-efficacy, task technology fit, information quality, attitude toward using GM, and effectiveness with regard to using GM) are studied in the research model, which has an impact on student adoption of GM at King Saud University (see Figure 1).

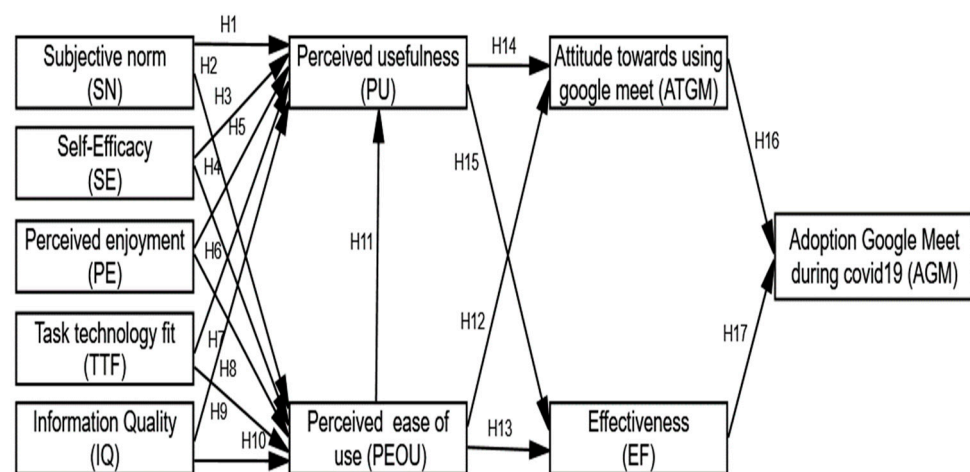


Figure 1. Research model.

2.1. Subjective Norms

When it comes to technology, the subjective norms (SN) are a strategy for determining whether other individuals with comparable views would or would not behave in the same

manner. The introduction of SN has strengthened the TAM model by allowing it to account for the actions of a group of users [51]. This study investigated SN as an external element that might explain why students would want to use GM in a meeting of classmates. Many pieces of research in the literature reporting on technology acceptability or adoption have used the influence of SN on behavioral intention, especially on PU and PEOU [50,52,53]. One of the most recent pieces of research to employ TAM and SN as an external factor is that of [54], which emphasizes the strong relationship between the external variables and other embedded TAM elements noted in previous studies [55]. However, it appears that the SN external component has not been fully and effectively utilized in these investigations. As a result, the goal of this study was to establish a link between SN as an external factor, and another external element that has a significant impact on the individual.

2.2. Self-Efficacy

The concept of self-efficacy is frequently employed as a personal element. It is described as people's assessments of their ability to plan and carry out the steps necessary to achieve specific sorts of performances [56]. It does not represent actual abilities or skills, but rather a person's belief in their capacity to do or execute a skill [57]. In terms of specificity and direct relationship with performance tasks, self-efficacy differs from motivational concepts, such as result expectancies, self-control, and control beliefs, and is a better predictor of academic accomplishment [58]. In a number of studies, self-efficacy has been identified as one of the most significant indicators of student involvement, education, and accomplishment [59]. Furthermore, self-efficacy is drawn from four major sources of data: performance achievement, emotional arousal, motivation, and physiological conditions [56,60]. This study points out that it has been clearly established in both previous and current studies that GM has made a significant contribution to teaching and learning, which many academics see as being successful and efficient when it comes to online education [13,61].

2.3. Task Technology Fit

The attitude towards utilizing an information system to fulfill various activities is measured by perceived technological fit. Previous research has used the task technology fit model to assess the performance of technology used to complete tasks, as well as to assess the technology's efficacy in completing given tasks and the level of pleasure it offers users [62,63]. This involves gaining a better knowledge of how task technology fit (TTF) may impact e-learning efficiency and satisfaction according to studies done under this section [64,65]. Someone else has looked at perceptions of online learning's fit with academic assignments and the perceived influence of using Google Meet on perceived performance [66,67]. The importance of task–technology fit in LMS success according to [68] tackles the subject of how task–technology fit affects the student performance impacts of LMS. Investigating the influence of the Google Meet mainstream press lecture technique on improving student knowledge and learning outcomes while studying from home [69,70] is what the researchers wrote about.

2.4. Information Quality

Several researchers in the field of e-learning have implemented the information systems success model to analyze the link between educational quality features, satisfaction, and the continued utilization of information systems [71]. Information and knowledge quality, for example, have a beneficial impact on user satisfaction, knowledge adoption, and the desire to consume and contribute information in an online community [72,73]. It relates to information quality success to describe knowledge sharing behavior in knowledge management systems, according to [73,74]. The quality of the information influences knowledge management systems' (KMS) self-efficacy, which in turn influences information intentions. Students' attitudes toward utilizing GM websites, and the effectiveness in GM with regard to online learning contexts, are influenced by perceived information quality

and computer self-efficacy. As a result, information quality parameters PEOU, and PU have a favorable association.

2.5. Perceived Enjoyment

The term ‘perceived pleasure’ may be defined as a range of services or actions provided by a learning management system (LMS) that are designed to be delightful in and of themselves, independent of expected performance outcomes [75]. As a result, the extent to which a student feels that using social media boosts their academic achievement using the GM app [76] is defined in this study as perceived delight. A user’s participation in online social media sites is more likely if the procedure is enjoyable. Through a suggestion to combine the TAM model with the theory of motivation, an inquiry was done in identifying the behavior to adopt in students on an internet-based learning medium (ILM) in the work of [77]. In addition to perceived utility and perceived ease of use for TAM, the study looked at felt pleasure as a key catalyst [78,79]. All of the outcomes revealed evidence of felt enjoyment, including the importance of the perceived usefulness impact in influencing students’ attitudes and ILM’s usage intention. They will progressively build their attitude with regard to technology and their acceptance/adoption of it. As a result, pleasure may be characterized as a personal sensation produced independently of any other effects, and it can be linked to the perceived utility that users can develop. To develop the acceptance theory, fun or enjoyment might be introduced as a construct [39,52,80]. As a result, one must take into account the preceding premise that perceived satisfaction is a key determinant.

2.6. Perceived Usefulness

Many academics have lately adopted the TAM model to assess the impact of technological acceptance and adoption [49,81,82]. The TAM model’s two dimensions, perceived ease of use and perceived usefulness, are critical in determining the impact of technology on its users in the educational sector [52,81,82]. The degree to which an individual feels that employing a certain technology would improve his or her job performance is known as perceived usefulness [49]. This indicates that how users view the value of technology in teaching and how learning shapes their attitudes about computer use, whether positive or negative. The behavioral desire to utilize Google Classrooms is likewise influenced positively and significantly [83,84]. The purpose of this study was to see if an online exam could be used to measure students’ willingness to adapt to Google Meet. As a result of technical awareness and social value, technology-oriented online education is deemed to be valuable.

2.7. Perceived Ease of Use

According to research by [49], perceived utility and simplicity of use are determined by technology adoption and students’ response systems [85]. Many academics have lately employed the TAM model to assess the impact of technological acceptance and adoption [49,85]. The TAM model’s two dimensions, perceived ease of use and perceived usefulness, are critical in determining the impact of technology on its users in the educational sector [2,11,86]. As a result, PEOU and PU may be employed as mediators to assess the acceptability of Google Meet on the one hand, and the impact of the perceived enjoyment (PE) on the other. As a result, when consumers’ perceptions of technology are rated as it being easy to use, it means they are ready to accept it, and they will acquire favorable attitudes toward technology and their understanding of technological concepts. Similarly, ease of use perception influences PU and leads to technological acceptance.

2.8. Attitude towards Using Google Meet

The rapid rise of blended learning in higher education has been identified as a prominent problem in terms of keeping students engaged and enthusiastic about online learning [87]. Students’ intentions to learn online were impacted greatly by their perceived usefulness, enjoyment of the activity, and demonstrating a positive attitude [88]. Positive

attitudes toward learning can guide behavior and positive attitudes toward learning, which can aid in the efficient application of knowledge techniques [68,89]. Students have a positive attitude toward education because it has a beneficial influence on their achievement and self [90]. Student and teacher attitudes and skills are influenced by technology accessibility, which is favorably correlated with technology use [91]. Furthermore, positive sentiments with regard to ICT and eLearning were essentially equal among female and male students [92]. It is reasonable to suppose that, if students have a favorable attitude toward examinations, they will also have a positive attitude regarding adaptability. This is hypothesized based on the above-mentioned literature.

2.9. Effectiveness of Utilizing Google Meet

The extent to which learning outcomes are attained might be characterized as learning effectiveness. According to one study [93], there is a favorable relationship between learning effectiveness and real grades. We can model and evaluate the links among the components that influence learning effectiveness after they've been discovered. The growing popularity of online learning has piqued the interest of various scholars who want to investigate its efficacy. Pre- and post-tests are used in the majority of studies on the issue [94,95]. Facilitating e-learning does not ensure that the desired learning results are achieved. In order to attain the appropriate level in terms of results, learners must participate. Several studies have compared whether e-learning is more successful than face-to-face learning [96]. However, from a theoretical standpoint, there are few studies on the components that influence learning efficacy [97]. Identifying the elements that influence learning effectiveness benefits, not only concerning the online learning via Google Meet providing organizations, but also concerning the students, because both stakeholders may utilize it to improve learning results. The key reason is because the language instruction tool is inexpensive to obtain relative to other learning management systems (LMS) [9]. According to research, GM is a free Google service that is simple to set up; it is stated that, with the new upgrade from Google Talk to Google Meet, this allows it to compete strongly with Skype and Zoom, and it is one of the top tools for team teleconferencing [98].

2.10. Adoption of Google Meet for Education

The adoption of the internet in Saudi Arabia began in the 1990s, with colleges being the first to do so. The technology eventually spread to all of the country's campuses [3,99]. Information and communication technology (ICT) is widely used in developed countries, such as the United States, at institutions with university degree programs. Both students and professors gain from the use of ICT to facilitate learning [21]. The use of online meetings, such as the Google Meetings tool, aids time management by allowing students and instructors to interact both synchronously and asynchronously. However, instructors' attitudes toward students can be a barrier to Google Meet uptake, especially when working with students who are unfamiliar with using online meeting technologies [100]. Educators do not believe online meetings to be successful teaching tools; instead, they rely on conventional methods that have been demonstrated to be ineffective when compared to new solutions. Instead of encouraging a student to utilize ICT to better their knowledge, an instructor may dismiss the student or refuse to assist them [28]. According to the author, this is a problem that most students experience. Furthermore, some professors lack technical abilities, which causes students to be inconvenienced [100]. On the other hand, individuals from various cities and regions may also readily meet inside a virtual environment, enabling the creation of distinct and quite diversified classrooms inside a single nation, or even in terms of numerous countries. Due to the closure of all educational institutions in Saudi Arabia, an unanticipated quick change from the conventional 'traditional' learning style [101] to the new government-endorsed strategy in the form of online learning, has occurred.

3. Research Methodology

Technology during COVID-19 is approaching closer to effectively facilitate the process of teaching. Coined by the fact that GM was one of the influential approaches to replace the face to face teaching environment within the breakdown period, Google Meet is a face-to-face conference platform where educators and students can interact directly as they meet face-to-face. In this application, there are many advantages, such as file sharing in PDF format, that can be done easily. It is a great tool for posting new assignments. It is also a good way to get the class to interact. They can upload specific questions to be answered by students in stream. Moreover, Google Meet offers the easiest facilities for individuals who want to participate in conferences or meetings with just a link or room number. Google online format also includes two-way live broadcast lectures. Google meet makes online courses very popular due to saving time, costs, and impact towards the environment. GM requires low financial cost and offers a good webinar experience. The use of GM also allows participants to write and discuss together throughout the process. Google Meet can also be used for community-based discussions, etc. Thus, Google Meet affords opportunities for participation in learning during online teaching. It offers a space for virtual meeting (Google Meet) and to host virtual lessons (Google Classroom). Although Google Classroom touts its potential for transformative instruction, the technological design of Google Meet encourages replication of many pedagogies already used in education. By providing the option for students to comment, it is possible for teachers to get feedback on how assignments and resources are being received, allowing for future work to be focused in a way that will best engage the students.

3.1. Study Design

The study's main purpose was to develop a simple and easy-to-understand conceptual model for evaluating social media acceptability and the factors that influence it. A multi-stage testing strategy was used to construct, validate, and test the suggested model and survey. To begin with, participants tested twenty-nine (29) previously used questions to evaluate the adoption of GM for educational purposes at Saudi educational institutions, and 10 components were extracted to determine the adoption of GM for learning. Second, data were obtained from 208 students, both local and international, who were chosen at random at the College of Education at King Saud University. The components in the questionnaire, which included parts of assessment information system success models, were rated using a five-point Likert scale information system success model (ISSM). The study was empirical, with the proposed conceptual model of social media usage experimentally evaluated using structural equation modeling (SEM), as described by [102]. Suitable statistical tests were employed to validate the findings and demonstrate significance in terms of the outcomes of this study. The survey was carried out individually, and participants were invited to return it after they were finished. The survey focused on user happiness and the respondents' perceptions of its impact on social media usage. SPSS with partial least square structural equation modeling was utilized for data analysis (Smart PLS 3.3.3).

3.2. Data Gathering

The data were collected from students at King Saud University in Saudi Arabia. A questionnaire survey was used to obtain the necessary data. A total of 215 students were chosen to take part in the survey. The study required a sample size of 208 individuals. As a result, the sample size in this study is appropriate as an exploratory study for portraying postgraduate students at the College of Education in King Saud University in terms of GM acceptance. About seven survey responses were discarded due to missing information. From a total of 208 surveys, the data were analyzed using SPSS. The students who took part in the survey came from the college of education. The researcher discussed the study's objectives and the description of online meetings, such as GM, at the start of the data collecting procedure, and the students then answered the survey. Table 1 shows the gender, age, specialization, and use of Google Meet (GM) rates among the respondents. According

to the survey's demographics, women made up 55 (26.4 percent) of the respondents, while men made up 153 (73.6 percent). 11 (5.3%) of those polled were between the ages of 18 and 20. 30 (14.4%) were between the ages of 21 and 24. 73 (35.1%) were between the ages of 25 and 29. 48 (23.1%) were between the ages of 30 and 34. 23 (11.1%) were between the ages of 35 and 40. 12 (5.8%) were between the ages of 41 and 45. Finally, 11 of the respondents (5.3%) were 46 or older.

Table 1. Demographic profile.

Demographic	Description	N	%	Cumulative %
Gender	Male	153	73.6	73.6
	Female	55	26.4	100.0
Age	18–20	11	5.3	5.3
	21–24	30	14.4	19.7
	25–29	73	35.1	54.8
	30–34	48	23.1	77.9
	35–40	23	11.1	88.9
	41–45	12	5.8	94.7
	46 and Above	11	5.3	100.0
Specialization	Education technologies	60	28.8	99.5
	Special Education	45	21.6	70.7
	educational administration	69	33.2	49.0
	Curriculum and Instruction	33	15.9	15.9
	Others	1	0.5	100.0
Use of GM	I currently use it	202	97.1	97.1
	I have not used it	6	2.9	100.0

3.3. Instrument Development

A five-point Likert scale was used to gather data, and the preexisting constructs of this research were used with the following adjustments to meet the context of this study: subjective norm (SN) was adapted from the sample questionnaire from [55,103], self-efficacy was adapted from the sample questionnaire from [57,59,89], perceived enjoyment was adapted from [11,68], task-technology fit was adapted from the sample questionnaire from [66,68], information quality was considered [89], and perceived ease of use and perceived usefulness were adapted from the sample questionnaire from [55,66,104], Attitude with regards to using GM was adapted from [68,89]. Effectiveness was adapted from the sample questionnaire from [9]. Finally, adoption of GM for education was adapted from the sample questionnaire from [16,105]. Tables 2 and 3 presents all variables and their sources.

Table 2. Reflective indicator loadings, internal consistency reliability, and convergent validity.

Construct	Load	Alpha	CR	AVE
Subjective norm (SN)	0.813	0.907	0.931	0.728
	0.880			
	0.852			
	0.874			
	0.847			
Self-Efficacy (SE)	0.864	0.925	0.943	0.769
	0.874			
	0.877			
	0.894			
	0.876			

Table 2. *Cont.*

Construct	Load	Alpha	CR	AVE
Perceived enjoyment (PE)	0.805	0.898	0.925	0.711
	0.818			
	0.859			
	0.878			
	0.853			
Task technology fit (TTF)	0.837	0.912	0.934	0.739
	0.874			
	0.878			
	0.870			
	0.838			
Information Quality (IQ)	0.868	0.910	0.933	0.735
	0.860			
	0.882			
	0.880			
	0.796			
Perceived usefulness (PU)	0.809	0.862	0.901	0.644
	0.788			
	0.780			
	0.819			
	0.818			
Perceived ease of use (PEOU)	0.871	0.929	0.947	0.780
	0.860			
	0.897			
	0.900			
	0.888			
Attitude towards using G M (ATGM)	0.847	0.900	0.926	0.716
	0.877			
	0.877			
	0.789			
	0.836			
Effectiveness of using GM (FE)	0.905	0.935	0.951	0.794
	0.879			
	0.905			
	0.903			
	0.861			
Adoption of G M for education (AGM)	0.881	0.936	0.951	0.796
	0.906			
	0.895			
	0.889			
	0.889			

Table 3. Fornell-Larcker criterion.

	AGM	ATGM	FE	IQ	PEOU	PE	PU	SE	SN	TTF
Adoption of G M for education (AGM)	0.892									
Attitude towards using G M (ATGM)	0.587	0.846								
Effectiveness of using G M (FE)	0.556	0.590	0.891							
Information Quality (IQ)	0.516	0.573	0.816	0.857						
Perceived ease of use (PEOU)	0.569	0.697	0.665	0.670	0.883					
Perceived enjoyment (PE)	0.608	0.648	0.687	0.677	0.701	0.843				
Perceived usefulness (PU)	0.658	0.798	0.684	0.696	0.735	0.736	0.803			
Self-Efficacy (SE)	0.663	0.665	0.604	0.577	0.683	0.677	0.703	0.877		
Subjective norm (SN)	0.610	0.633	0.714	0.680	0.674	0.682	0.714	0.632	0.853	
Task technology fit (TTF)	0.561	0.610	0.558	0.546	0.627	0.678	0.652	0.650	0.515	0.860

4. Data Analysis and Results

4.1. Measurement Model

The assessment processes used to verify the measurements' reliability and validity are referred to as the measurement model. Three different measures were considered. There are three types of validity: discriminant validity, convergent validity, and indicator loadings and internal consistency reliability. Hair et al. recommend three measures [102].

4.2. Internal Consistency Reliability and Indicator Loadings

In this research, the PLS-SEM results were employed to determine indicator loadings. The details of the loadings are shown in Tables 2 and 3. The bulk of the items had loading levels greater than 0.700 [102]. In the second phase of the PLS-SEM investigation, fifty indicators were assessed. Internal consistency reliability refers to the assessment findings for statistical consistency among variables. Cronbach's alpha (CA) and composite reliability (CR) should be used to assess internal reliability. The CA and CR values in this study were determined by using the [102] criteria: >0.700 for CA and >0.700 for CR. Table 2 shows the characteristics of each measurement value. CA and CR values show strong internal consistency across the board, with CA reliability extending from 0.862 to 0.936, and CR confidence ranged from 0.901 to 0.951 for all constructions.

4.3. Convergent Validity

Validity testing is a statistical method relating to construct validity. According to the concept of convergent validity, evaluations utilizing the same or comparable conceptions should be substantially connected. The AVE scores must be given in terms of convergent validity. The SmartPLS scores were calculated using a PLS-SEM technique. The AVE score should be more than, or equal to, 0.500, and it should explain at least 50% of the variation. The AVE value for all constructions is larger than 0.500, which accounts for more than half of the difference (Table 2).

4.4. Discriminant Validity

Discriminant validity, according to [102], is the degree to which a construct differs from other constructs. The AVE score of a concept must be smaller than the shared variance for all constructs in the model. According to the findings of the study, each concept's AVE score is lower than their shared variance (Table 2). As a consequence of examining the Fornell-Larcker criteria, discriminant validity was established. Cross-loadings can also be used to assess discriminant validity. All indicators' outer loading values for each construct were bigger than their cross-loading values for the other constructs, as shown in Table 3. As a result of the cross-loading value evaluation, discriminant validity was established. Discriminant validity will also appear when the heterotrait–monotrait (HTMT) is higher than 0.900. HTMT above 0.900 refers to a lack of discriminant validity. All of the HTMT readings in Table 4 were less than 0.900. The results show that the values were substantially different from 1.

Table 4. Heterotrait–monotrait (HTMT).

	AGM	ATGM	FE	IQ	PEOU	PE	PU	SE	SN
Adoption of G M for education (AGM)									
Attitude towards using G M (ATGM)	0.635								
Effectiveness of using G M (FE)	0.591	0.642							
Information Quality (IQ)	0.559	0.633	0.886						
Perceived ease of use (PEOU)	0.607	0.758	0.708	0.726					
Perceived enjoyment (PE)	0.663	0.72	0.747	0.749	0.765				
Perceived usefulness (PU)	0.73	0.704	0.761	0.786	0.818	0.834			
Self-Efficacy (SE)	0.709	0.728	0.647	0.628	0.733	0.741	0.786		
Subjective norm (SN)	0.661	0.7	0.775	0.748	0.733	0.755	0.806	0.689	
Task technology fit (TTF)	0.607	0.673	0.602	0.601	0.678	0.747	0.733	0.707	0.566

4.5. Structural Model Assessment

There are several stages to the structural model evaluation [102]. The reporting of the variance inflation factor (VIF) data was the first step in the computerization of collinearity. In the second step, the link was investigated. In step three, the significance level (R^2) was calculated. The effect size of f^2 for the construct's relevance was given in step four. The purpose was to investigate the explanation of the endogenous constructs that were chosen. The data were also generated in PLS-SEM utilizing the pegging process for the R^2 and f^2 impact sizes when displaying the Q2 values.

4.6. Collinearity Issue

Serial correlation between the sets of predictors should be investigated. The serial correlation is determined by looking at the VIF value. If the VIF value is stated to be >3000 , serial correlation will be a concern [102]. Attitude toward using GM (ATGM) is a predictor of GM adoption for education (AGM) (VIF = 1.233); effectiveness of using GM (FE) is a predictor of GM adoption for education (VIF = 1.534); information quality (IQ) is a predictor of ease of use (PEOU) (VIF = 2.260); and perceived usefulness (PU) (VIF = 2.382) is considered. Perceived enjoyment (PE) is a predictor of perceived usefulness (PU) (VIF = 2.020) and ease of use (PEOU) (VIF = 2.936); self-efficacy (SE) is a predictor of usefulness (PU) (VIF = 2.472) and ease of use (VIF = 2.331); and task technology fit (TTF) is a predictor of usefulness. VIF values are all less than three (Table 5). As a result, collinearity is not a problem in this study [102].

Table 5. Variance inflation factor (VIF).

	AGM	ATGM	FE	IQ	PEOU	PE	PU
Adoption of GM for education (AGM)							
Attitude towards using GM (ATGM)	1.534						
Effectiveness of using GM (FE)	1.534						
Information quality (IQ)					2.260		2.382
Perceived ease of use (PEOU)		2.178	2.178				2.775
Perceived enjoyment (PE)					2.936		2.020
Perceived usefulness (PU)		2.178	2.178				
Self-efficacy (SE)					2.331		2.472
Subjective norm (SN)					2.398		2.503
Task technology fit (TTF)					2.139		2.200

4.7. Hypothesis Testing

The data were bootstrapped via 5000 sub-samples to determine the route coefficient between endogenous and exogenous components. Figure 1 shows the hypothesis, Figure 2 shows the path coefficient results, and Figure 3 shows the path (T-Values) results. SEM analysis was utilized to test the model suggested in this study. In order to evaluate the influence of the TAM model with four external factors on attitude toward utilizing GM and efficacy of GM usage, which can affect acceptance of GM for learning, seventeen hypotheses were tested in the research model. The findings, as shown in Table 4, backed up all of the study model's hypotheses. The perceived usefulness and perceived ease of use of GM for education were significantly influenced by subjective norms (H1 = 0.196, $t = 2.623$; H2 = 0.195, $t = 2.337$). Hypotheses H1 and H2 are, therefore, accepted. The third and fourth hypotheses claimed that self-efficacy had a substantial favorable impact on perceived utility and perceived ease of use while using GM for educational purposes (H3 = 0.164, $t = 2.671$; H4 = 0.225, $t = 3.453$). Hypotheses H3 and H4 are, therefore, confirmed. Perceived enjoyment was positively connected to perceived utility and perceived ease of use for using GM for educational purposes (H5 = 0.162, $t = 2.047$; H6 = 0.174, $t = 2.051$), according to the data in Table 3. As a result, H5 and H6 were endorsed. Furthermore, task-technology fit (TTF) was strongly connected to perceived utility and perceived ease of use for using GM for educational purposes (H7 = 0.127, $t = 2.036$; H8 = 0.148, $t = 2.119$), supporting

H7 and H8. In addition to the above findings, the ninth and tenth hypotheses (H9 and H10), which assumed a positive and significant relationship between information quality and perceived utility and perceived ease of use for using GM for educational purposes (H9 = 0.162, t = 2.409; H10 = 0.209, t = 2.608), were also supported. The hypotheses of a link between perceived ease of use and perceived usefulness (H11 = 0.189, t = 2.923), and attitude toward utilizing G M (H12 = 0.239, t = 3.920), and the efficacy of G M use (H13 = 0.353, t = 4.254), are all supported. Furthermore, the hypothesis of a link between perceived usefulness and attitude toward utilizing GM (H14 = 0.622, t = 10.504), as well as the efficacy of GM usage (H15 = 0.424, t = 5.285), are supported. The adoption of GM for education was positively connected to attitude about utilizing it (H16 = 0.397, t = 5.914). As a result, H16 was endorsed. The hypothesis that attitude mediates between perceived ease of use and perceived utility was confirmed in terms of factors directly impacting the adoption of GM. Furthermore, the efficacy of utilizing GM was positively connected to GM adoption for educational purposes (H17 = 0.321, t = 4.297). The hypothesis that the efficacy of utilizing GM mediators between perceived ease of use and perceived usefulness was validated in terms of factors directly impacting the adoption of using GM for educational purposes. All of the hypotheses were found to be true. Table 6 shows the results.

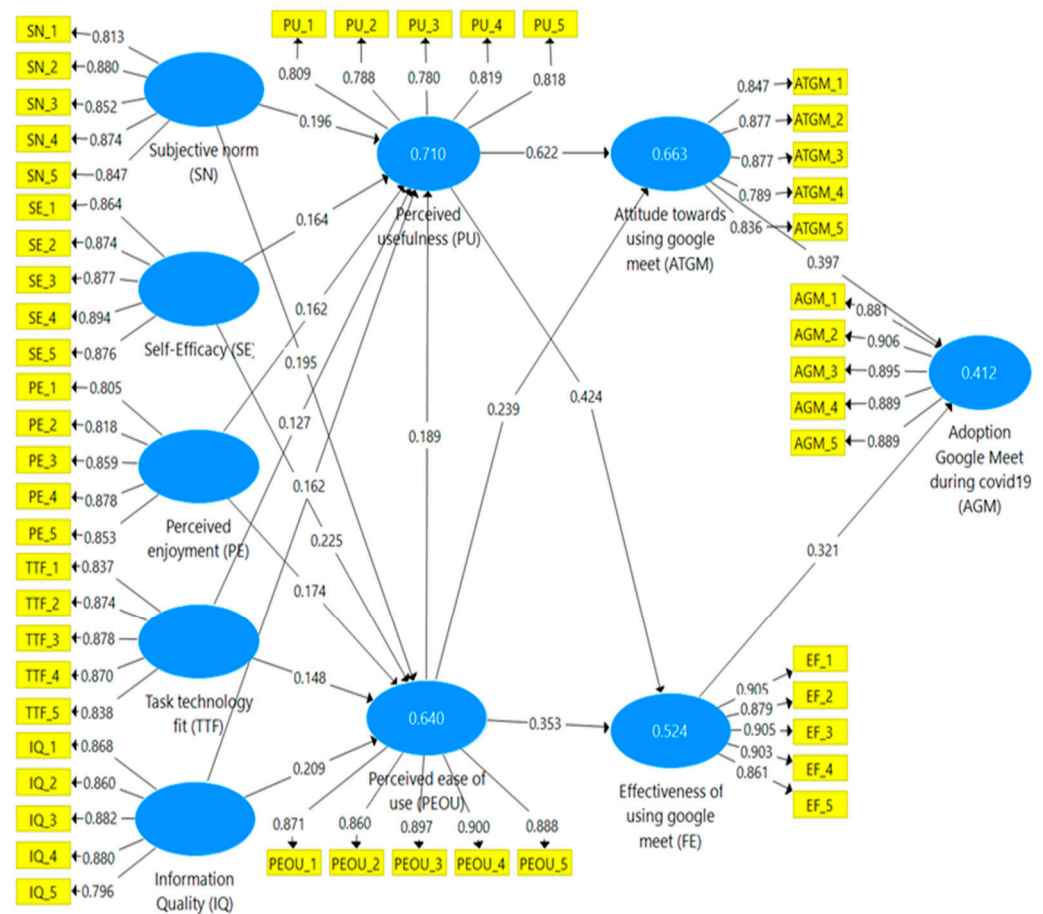


Figure 2. Path coefficient findings.

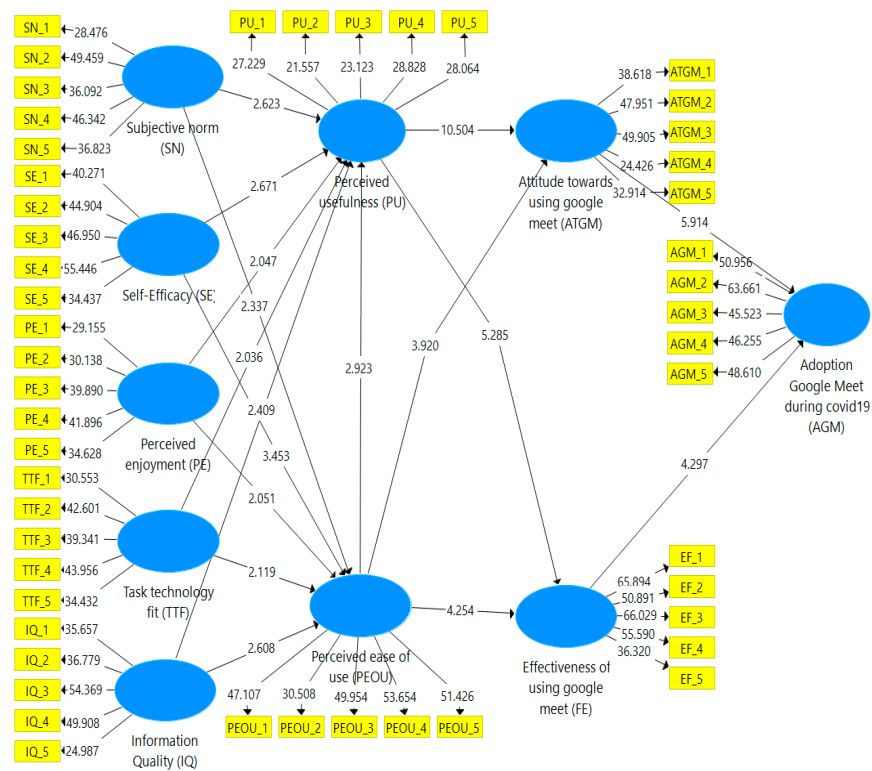


Figure 3. Findings for Path (T-Values).

Table 6. Structural model for hypothesis testing results.

H	Factors	β	T-Values	p-Values
H1	Subjective norm (SN) → Perceived usefulness (PU)	0.196	2.623	0.009
H2	Subjective norm (SN) → Perceived ease of use (PEOU)	0.195	2.337	0.019
H3	Self-Efficacy (SE) → Perceived usefulness (PU)	0.164	2.671	0.008
H4	Self-Efficacy (SE) → Perceived ease of use (PEOU)	0.225	3.453	0.001
H5	Perceived enjoyment (PE) → Perceived usefulness (PU)	0.162	2.047	0.041
H6	Perceived enjoyment (PE) → Perceived ease of use (PEOU)	0.174	2.051	0.040
H7	Task technology fit (TTF) → Perceived usefulness (PU)	0.127	2.036	0.042
H8	Task technology fit (TTF) → Perceived ease of use (PEOU)	0.148	2.119	0.034
H9	Information quality (IQ) → Perceived usefulness (PU)	0.162	2.409	0.016
H10	Information quality (IQ) → Perceived ease of use (PEOU)	0.209	2.608	0.009
H11	Perceived ease of use (PEOU) → Perceived usefulness (PU)	0.189	2.923	0.003
H12	Perceived ease of use (PEOU) → Attitude towards using GM (ATGM)	0.239	3.920	0.000
H13	Perceived ease of use (PEOU) → Effectiveness of using GM (FE)	0.353	4.254	0.000
H14	Perceived usefulness (PU) → Attitude towards using GM (ATGM)	0.622	10.504	0.000
H15	Perceived usefulness (PU) → Effectiveness of using GM (FE)	0.424	5.285	0.000
H16	Attitude towards using GM (ATGM) → Adoption of GM for education (AGM)	0.397	5.914	0.000
H17	Effectiveness of using GM (FE) → Adoption of GM for educational purposes (AGM)	0.321	4.297	0.000

4.8. Coefficient of Determination (R²)

The significance level (R²), which is the output result of the analysis of regression, is understood as the variance percentage in endogenous constructs that may be predicted by the exogenous variable. It evaluates the accuracy of a proposed model’s predictions. The square of the correlation constructs is used to compute it. The R² scale runs from 0 to 1, with a greater number indicating a higher level of R². A value of 0.25 is considered weak, 0.50 is moderate, and 0.75 is significant [102]. Table 7 shows the R² result based on the study’s findings. The adoption of GM for educational purposes (AGM) (0.412, Moderate), attitude towards Google Meet (ATGM) (0.663, Moderate), effectiveness of Google Meet (FE)

(0.524, Moderate), PEOU, (0.640, Moderate), and PU (0.412, Moderate) (0.710, High) are considered. Table 7 shows the results.

Table 7. Coefficient of determination (R^2).

	R Square	Results
Adoption of GM for educational purposes (AGM)	0.412	Moderate
Attitude towards using GM (ATGM)	0.663	Moderate
Effectiveness of using GM (FE)	0.524	Moderate
Perceived ease of use (PEOU)	0.640	Moderate
Perceived usefulness (PU)	0.710	High

4.9. Effect Size (F^2)

The correlation value, or F^2 , is a statistical term that measures the strength of a predictor construct's link with a variable. To put it another way, F^2 is used to assess the impact of exogenous constructions on endogenous constructs. F^2 investigates how the R^2 value changes when an external component is excluded from the model. According to [102], the F^2 value of 0.02 is defined as an insignificant effect, the value of 0.15 as a medium impact, and the value of 0.35 as a significant effect. Seven confirmatory factor effect sizes were discovered in the study's data. The lowest influence was found when task technology fit to perceived usefulness gained the smallest effect, while the biggest F^2 was found when perceived usefulness to attitude toward utilizing Google Meet was met, with a value of 0.528 (See Table 8).

Table 8. F^2 result.

	F^2	Results
Subjective norm—> Perceived usefulness	0.053	Small
Subjective norm—> Perceived ease of use	0.044	Small
Self-Efficacy—> Perceived usefulness	0.038	Small
Self-Efficacy—> Perceived ease of use	0.061	Small
Perceived enjoyment—> Perceived usefulness	0.030	Small
Perceived enjoyment—> Perceived ease of use	0.029	Small
Task technology fit—> Perceived usefulness	0.025	Small
Task technology fit—> Perceived ease of use	0.028	Small
Information quality—> Perceived usefulness	0.038	Small
Information quality—> Perceived ease of use	0.054	Small
Perceived ease of use—> Perceived usefulness	0.045	Small
Perceived ease of use—> Attitude towards using GM	0.078	Small
Perceived ease of use—> Effectiveness of using GM	0.120	Small
Perceived usefulness—> Attitude towards using GM	0.528	Large
Perceived usefulness—> Effectiveness of using GM	0.174	Medium
Attitude towards using G M—> Adoption of GM for educational purposes	0.175	Medium
Effectiveness of using GM—> Adoption of GM for educational purposes	0.114	Small

5. Discussion and Implementations

This study explored how university students felt about using, adopting, and accepting online emergency learning. A constructive and extended TAM was effectively employed in this study to describe the framework experienced by students when they adopted GM for education in order to explore aspects impacting the usage of GM for educational purposes. According to one study, the use of GM can assist students to participate in deeper learning and grasp the meaning of a given topic by stimulating their knowledge of the critical exploratory process [11]. The goal of this study was to create a new model that would illustrate 10 criteria and test 18 hypotheses for using GM for learning. The following are the results: the first element is the subjective norm. This had two hypotheses (H1 and H2) that had substantial beneficial effects on the students' perceptions of Google Meet's

adoption utility and simplicity of use. This is consistent with previous research, which has established a positive association between subjective norm and perceived utility and ease of use [16,55,106–108]. However, these findings contradicted those of a previous study [55,109]. The third element is self-efficacy, which had two hypotheses (H3 and H4) that had substantial favorable effects on the students' perceptions of Google Meet's adoption utility and simplicity of use. This is in line with previous research [16,57,60] that revealed a positive association between subjective norm and perceived usefulness and perceived ease of use. Furthermore, the following variable is perceived pleasure, which had two hypotheses (H5 and H6) that had substantial favorable effects on the students' perceptions of Google Meet's adoption's perceived utility and simplicity of use. This is in line with previous research [11,26,109], which revealed that reported enjoyment had a positive association with perceived usefulness and perceived ease of use. Additionally, task-technology-fit, related to two assumptions (H7 and H8) that had substantial positive impacts on the students' perceived usefulness and perceived ease of use of Google Meet adoption was the following factor. This is in line with previous research, which demonstrated a favorable association between task technology fit and perceived utility and ease of use [2,68]. However, these findings contradicted those of a previous study [66,110]. The second component is information quality, which had two hypotheses (H9 and H10) with substantial positive impact on adolescents' perceptions of Google Meet's adoption utility and simplicity of use. This is in line with previous research [73,89], which revealed that information quality had a positive association with perceived utility and perceived ease of use. The next variable is considered to be the ideal of use, which had three hypotheses (H11, H12, and H13) with substantial positive impacts on the students' perceived usefulness, as well as attitude towards using Google Meet and the effectiveness of Google Meet adoption. This is in line with previous research, which demonstrated a positive association between perceived utility and reported ease of use [16,66,89]. The next element is perceived usefulness, which already had two hypotheses (H14 and H15), with substantial positive impacts on attitude toward utilizing GM and the effectiveness of GM adoption. This is in line with previous research, which demonstrated a positive association between perceived utility and reported ease of use [16,66,89]. The mediating variable is user attitude toward Google Meet, which had one hypothesis (H16) that had a substantial beneficial impact on the adoption of GM for educational purposes. This is similar to previous research, which revealed a favorable association between attitude toward utilizing GM and use of GM for educational purposes [60,89,103]. Finally, the mediating component is Google Meet efficacy, which had one hypothesis (H17) that it had substantial positive impacts on Google Meet adoption for educational purposes. This is in line with previous research, which revealed a positive association between the effectiveness of utilizing GM and the acceptance of GM for educational purposes [9,111]. The results of this study show that the abrupt move to online learning went smoothly, and that current instructional resources were prepared for the change. Communication with coworkers and academics was simple, and they had no problems communicating with one another. This was due to the availability and diversity of social media applications, such as Google Meet and Zoom, that contributed to overcome the difficulties that one may have faced, especially during COVID-19 in Saudi Arabia [101]. The purpose of this study is to obtain better knowledge of how GM is used in education and how it relates to the subjects' subjective norms, self-efficacy, technological fit, information quality, and reported satisfaction with regard to using GM. Utility, perceived simplicity of use, attitude toward using GM, and effectiveness of using GM provide a backdrop that is aided by online learning that can increase students' acceptance with regard to using GM. According to the findings of this study, utilizing GM improves subjective norms, self-efficacy, task technology fit, information quality, perceived enjoyment, perceived usefulness, perceived ease of use, attitude toward using Google Meet, and efficiency with regard to using GM, all of which can help to increase adoption of GM for educational purposes, as noted in previous and present research [60,61,107]. As a result, perceived usefulness, ease of use, attitude toward using GM, and efficiency of someone using GM are all related

to subjective norms, self-efficacy, task technology fit, information quality, and perceived enjoyment, all of which help students accept distance classes by allowing them to obtain precious assets from their peers, such as their instructors' guidelines. When utilizing GM to communicate, empirical research reveals that on-campus students require more help beyond brief face-to-face conversations. According to the findings of the research, higher education learners' attitudes with regard to utilizing, plan to use, and contentment with online learning associated with GM showed a positive relationship with actual usage. It may be assumed that providing ideal conditions for learning, such as suitable facilities, a pleasant environment, and a fast internet connection, will make it simpler for students to adopt e-learning. The use of GM has also been demonstrated to be a reliable predictor of both utility and perceived simplicity of use over time [16,61,68,89]. Similarly, there is a need to look at the impact on education, not just with regard to GM, but also with regard to other teaching-based technologies.

5.1. Implications

Learners, institutions of higher learning, and politicians will all benefit from this research. Knowledge with regard to the function of GM uptake in education requires an understanding of the link between its use and its favorable influence on students' performance. The results are useful for people who want to improve online learning or the online learning technologies that are used in teaching and learning. This research adds to our knowledge of why students prefer to use Google Meet for educational purposes. Informed policy decisions with regard to educational technology deployment in tertiary institutions may be obtained through a better understanding of intention factors, student predisposition for online learning, and useful technology. The outcomes of this study will raise educational officials' understanding of the benefits of sophisticated technology, such as GM in research universities, and enable such universities to create an engaging and appropriate online learning environment for students. Additionally, instructors and students can consider GM as an informal learning tool that facilitates learning and social engagement. GM may be utilized as a supplemental learning tool by institutional administrators, policymakers, and teachers, and students can use it to teach and learn. Furthermore, we propose that educational institutions develop their own websites and groups on various online meeting sites and invite students to join these groups and pages. based on our findings, this might aid students to address educational challenges. Official email addresses can be used to join groups or sites. Such initiatives may decrease a student's research effort, which is a limitation, and, therefore, more efficiently promote advantageous class participation with peers, independent of place or time.

5.2. Limitations

There are a few drawbacks to this research that can be addressed in future research. To begin with, this study only looks at one type of technology (GM), although there are many others that deserve investigation, such as the Zoom app, Facebook, and Skype. Future research should focus on these apps in order to determine the primary factors that influence students' views and behavior with regard to them. Finally, additional key elements, such as system quality and usability, must be investigated, as well as their impact on students' approval of GM usage in education. In particular, considering these digital learning applications in the KSA would make significant contributions to understanding the elements that influence future technology acceptability, as well as future technology deployment planning.

6. Conclusions

The focus of this research was to determine the perceived usefulness, attitude toward using GM for education, and the effectiveness of using GM in Saudi Arabian higher education. In addition, the primary significant obstacles and challenges faced by students were mentioned in this study. The authors used the modified TAM framework to develop man-

ual questionnaires to gather information from students. The SEM method was employed to achieve this goal. As a result, by utilizing the TAM model, this study established six concrete hypotheses to explain the primary determinants driving distance learning acceptability. The suggested model's hypotheses were tested using the SEM technique. At King Saud University in Saudi Arabia, we distributed 208 questionnaires among postgraduate students. The data were analyzed using PLS-SEM. According to the findings, the TAM model structures with four external elements, in the form of subjective norms, self-efficacy, task technology fit, and information quality, play a key role in boosting the acceptability of GM uptake in Saudi educational institutions. According to the research, all criteria have a substantial impact on GM acceptability among learners. Thus, this research adds to the corpus of information, as well as understanding accepting practices. It may also aid in the acceptance and promotion of GM uptake among Saudi university students.

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Institutional Review Board Statement: Ethical review and approval were waived for this study due to this research having adopted a questionnaire from previous research. Please refer to Section 3.3—Instrumentation. Additionally, we distributed the questionnaire to the students we teach, as well as to students in other classes at the same university. Therefore, all the students who answered the questionnaire agreed once they responded. Those who did not agree to respond to the questionnaire were excluded.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Not applicable.

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References

1. Diaz-Núñez, C.; Sanchez-Cochachin, G.; Ricra-Chauca, Y. Impact of Mobile Applications for a Lima University in Pandemic. *Int. J. Adv. Comput. Sci. Appl.* **2021**, *12*, 752–758. [[CrossRef](#)]
2. Al-Rahmi, A.M.; Shamsuddin, A.; Alturki, U.; Aldraiweesh, A.; Yusof, F.M.; Al-Rahmi, W.M.; Aljeraiwi, A.A. The influence of information system success and technology acceptance model on social media factors in education. *Sustainability* **2021**, *13*, 7770. [[CrossRef](#)]
3. Khalil, R.; Mansour, A.E.; Fadda, W.A.; Almisnid, K.; Aldamegh, M.; Al-Nafeesah, A.; Alkhalifah, A.; Al-Wutayd, O. The sudden transition to synchronized online learning during the COVID-19 pandemic in Saudi Arabia: A qualitative study exploring medical students' perspectives. *BMC Med. Educ.* **2020**, *20*, 285. [[CrossRef](#)]
4. Ali, W. Online and Online Learning in Higher Education Institutes: A Necessity in light of COVID-19 Pandemic. *High. Educ. Stud.* **2020**, *10*, 16–25. [[CrossRef](#)]
5. Alismaiel, O.A.; Cifuentes-Faura, J.; Al-Rahmi, W.M. Social Media Technologies Used for Education: An Empirical Study on TAM Model During the COVID-19 Pandemic. *Front. Educ.* **2022**, *7*, 882831. [[CrossRef](#)]
6. Maheshwari, G. Factors affecting students' intentions to undertake online learning: An empirical study in Vietnam. *Educ. Inf. Technol.* **2021**, *26*, 6629–6649. [[CrossRef](#)]
7. Ebrahimi, S.S.; Yeo, K.J. The Use of Technology at Malaysian Public High Schools. *Merit Res. J.* **2018**, *6*, 54–60.
8. Al-Rahmi, A.M.; Al-Rahmi, W.M.; Alturki, U.; Aldraiweesh, A.; Almutairy, S.; Al-Adwan, A.S. Acceptance of mobile technologies and M-learning by university students: An empirical investigation in higher education. *Educ. Inf. Technol.* **2022**, *27*, 7805–7826. [[CrossRef](#)]
9. Ironsi, C.S. Google Meet as a synchronous language learning tool for emergency online distant learning during the COVID-19 pandemic: Perceptions of language instructors and preservice teachers. *J. Appl. Res. High. Educ.* **2022**, *14*, 640–659. [[CrossRef](#)]

10. Purwanto, E.; Tannady, H. The Factors Affecting Intention to Use Google Meet Amid Online Meeting Platforms Competition in Indonesia. *Technol. Rep. Kansai Univ.* **2020**, *62*, 2829–2838.
11. Al-Marouf, R.S.; Alshurideh, M.T.; Salloum, S.A.; AlHamad, A.Q.M.; Gaber, T. Acceptance of google meet during the spread of coronavirus by Arab university students. *Informatics* **2021**, *8*, 24. [[CrossRef](#)]
12. Mishra, L.; Gupta, T.; Shree, A. Online teaching-learning in higher education during lockdown period of COVID-19 pandemic. *Int. J. Educ. Res. Open* **2020**, *1*, 100012. [[CrossRef](#)] [[PubMed](#)]
13. Fuchs, K. The Difference Between Emergency Online Teaching and e-Learning. *Front. Educ.* **2022**, *7*, 921332. [[CrossRef](#)]
14. Silva, S.; Fernandes, J.; Peres, P.; Lima, V.; Silva, C. Teachers' Perceptions of Online Learning during the Pandemic: A Case Study. *Educ. Sci.* **2022**, *12*, 698. [[CrossRef](#)]
15. Faura-Martínez, U.; Lafuente-Lechuga, M.; Cifuentes-Faura, J. Sustainability of the Spanish university system during the pandemic caused by COVID-19. *Educ. Rev.* **2021**, *74*, 645–663. [[CrossRef](#)]
16. Al-Marouf, S.R.; Salloum, S.A.; Hassanien, A.E.; Shaalan, K. Fear from COVID-19 and technology adoption: The impact of Google Meet during Coronavirus pandemic. *Taylor Fr.* **2020**, *14*, 1–16. [[CrossRef](#)]
17. Al-Rahmi, W.M.; Yahaya, N.; Alturki, U.; Alrobai, A.; Aldraiweesh, A.A.; Omar Alsayed, A.; Kamin, Y. Bin Social media-based collaborative learning: The effect on learning success with the moderating role of cyberstalking and cyberbullying. *Interact. Learn. Environ.* **2020**, *30*, 1434–1447. [[CrossRef](#)]
18. Alavudeen, S.S.; Easwaran, V.; Mir, J.I.; Shahrani, S.M.; Aseeri, A.A.; Khan, N.A.; Almodeer, A.M.; Asiri, A.A. The influence of COVID-19 related psychological and demographic variables on the effectiveness of e-learning among health care students in the southern region of Saudi Arabia. *Saudi Pharm. J.* **2021**, *29*, 775–780. [[CrossRef](#)] [[PubMed](#)]
19. Aljuaid, H. Online learning of english language courses via blackboard at saudi universities during COVID-19: Challenges and difficulties. *J. Asia TEFL* **2021**, *18*, 780–799. [[CrossRef](#)]
20. Pires, C. Perceptions of Pharmacy Students on the E-Learning Strategies Adopted during the COVID-19 Pandemic: A Systematic Review. *Pharmacy* **2022**, *10*, 31. [[CrossRef](#)] [[PubMed](#)]
21. Radianti, J.; Majchrzak, T.A.; Fromm, J.; Wohlgemant, I. A systematic review of immersive virtual reality applications for higher education: Design elements, lessons learned, and research agenda. *Comput. Educ.* **2020**, *147*, 103778. [[CrossRef](#)]
22. Al-Maatouk, Q.; Othman, M.; Alsayed, A.O.; Al-Rahmi, A.M.; Abuhassna, H.M.; Al-Rahmi, W. Applying communication theory to structure and evaluate the social media platforms in academia. *Int. J. Adv. Trends Comput. Sci. Eng.* **2020**, *9*, 1505–1517. [[CrossRef](#)]
23. Altalhi, M. Toward a model for acceptance of MOOCs in higher education: The modified UTAUT model for Saudi Arabia. *Educ. Inf. Technol.* **2021**, *26*, 1589–1605. [[CrossRef](#)]
24. Camilleri, M.A.; Camilleri, A.C. The Acceptance of Learning Management Systems and Video Conferencing Technologies: Lessons Learned from COVID-19. *Technol. Knowl. Learn.* **2021**, *27*, 1311–1333. [[CrossRef](#)]
25. Al Zahrani, E.M.; Al Naam, Y.A.; AlRabeeah, S.M.; Aldossary, D.N.; Al-Jamea, L.H.; Woodman, A.; Shawaheen, M.; Altit, O.; Quiambao, J.V.; Arulanantham, Z.J.; et al. E-Learning experience of the medical profession's college students during COVID-19 pandemic in Saudi Arabia. *BMC Med. Educ.* **2021**, *21*, 443. [[CrossRef](#)]
26. Al-Rahmi, W.M.; Yahaya, N.; Alamri, M.M.; Alyoussef, I.Y.; Al-Rahmi, A.M.; Kamin, Y. Bin Integrating innovation diffusion theory with technology acceptance model: Supporting students' attitude towards using a massive open online courses (MOOCs) systems. *Interact. Learn. Environ.* **2021**, *29*, 1380–1392. [[CrossRef](#)]
27. Shahba, A.A.; Alashban, Z.; Sales, I.; Sherif, A.Y.; Yusuf, O. Development and Evaluation of Interactive Flipped e-Learning (iFEEL) for Pharmacy Students during the COVID-19 Pandemic. *Int. J. Environ. Res. Public Health* **2022**, *19*, 3902. [[CrossRef](#)] [[PubMed](#)]
28. Al-Rahmi, A.M.; Shamsuddin, A.; Alismaiel, O.A. Task-Technology Fit Model: The Factors Affecting Students' Academic Performance in Higher Education. *Univers. J. Educ. Res.* **2020**, *8*, 6831–6843. [[CrossRef](#)]
29. Viner, R.M.; Russell, S.J.; Croker, H.; Packer, J.; Ward, J.; Stansfield, C.; Mytton, O.; Bonell, C.; Booy, R. School closure and management practices during coronavirus outbreaks including COVID-19: A rapid systematic review. *Lancet Child Adolesc. Health* **2020**, *4*, 397–404. [[CrossRef](#)] [[PubMed](#)]
30. Alawamleh, M.; Al-Twait, L.M.; Al-Saht, G.R. The effect of online learning on communication between instructors and students during COVID-19 pandemic. *Asian Educ. Dev. Stud.* **2020**, *11*, 380–400. [[CrossRef](#)]
31. Bączek, M.; Zagańczyk-Bączek, M.; Szpringer, M.; Jaroszyński, A.; Woźakowska-Kapłon, B. Students' perception of online learning during the COVID-19 pandemic: A survey study of Polish medical students. *Medicine* **2021**, *100*, 1–6. [[CrossRef](#)] [[PubMed](#)]
32. Muflih, S.; Abuhammad, S.; Al-Azzam, S.; Alzoubi, K.H.; Muflih, M.; Karasneh, R. Online learning for undergraduate health professional education during COVID-19: Jordanian medical students' attitudes and perceptions. *Heliyon* **2021**, *7*, e08031. [[CrossRef](#)]
33. Pei, L.; Wu, H. Does online learning work better than offline learning in undergraduate medical education? A systematic review and meta-analysis. *Med. Educ. Online* **2019**, *24*, 1666538. [[CrossRef](#)]
34. Soltanimehr, E.; Bahrampour, E.; Imani, M.M.; Rahimi, F.; Almasi, B.; Moattari, M. Effect of virtual versus traditional education on theoretical knowledge and reporting skills of dental students in radiographic interpretation of bony lesions of the jaw. *BMC Med. Educ.* **2019**, *19*, 233. [[CrossRef](#)]

35. Baby, A.; Kannammal, A. Network Path Analysis for developing an enhanced TAM model: A user-centric e-learning perspective. *Comput. Human Behav.* **2020**, *107*, 106081. [[CrossRef](#)]
36. Al-Azawei, A.; Parslow, P.; Lundqvist, K. Investigating the effect of learning styles in a blended e-learning system: An extension of the technology acceptance model (TAM). *Australas. J. Educ. Technol.* **2017**, *33*, 1–23. [[CrossRef](#)]
37. Scherer, R.; Siddiq, F.; Tondeur, J. The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Comput. Educ.* **2019**, *128*, 13–35. [[CrossRef](#)]
38. Sobaih, A.E.E.; Hasanein, A.M.; Elnasr, A.E.A. Responses to COVID-19 in higher education: Social media usage for sustaining formal academic communication in developing countries. *Sustainability* **2020**, *12*, 6520. [[CrossRef](#)]
39. Al-rahmi, A.M.; Al-rahmi, W.M.; Alturki, U.; Aldraiweesh, A.; Almutairy, S.; Al-adwan, A.S. Exploring the factors affecting mobile learning for sustainability in higher education. *Sustainability* **2021**, *13*, 7893. [[CrossRef](#)]
40. Abdulrahim, H.; Mabrouk, F. COVID-19 and the Digital Transformation of Saudi Higher Education.: Discovery Service para Universidad de Monterrey. *Asian J. Distance Educ.* **2020**, *15*, 291–306.
41. Niciporuc, T. Comparative analysis of the engagement rate on Facebook and Google Plus social networks. In Proceedings of the International Academic Conferences, New Orleans, LO, USA, 19–22 October 2014; pp. 334–339.
42. Lewandowski, M. Creating virtual classrooms (using Google Hangouts) for improving language competency. *Lang. Issues* **2015**, *26*, 37–42.
43. Wiyono, B.B.; Indreswari, H.; Putra, A.P. The Utilization of “Google Meet” and “Zoom Meetings” to Support the Lecturing Process during the Pandemic of COVID-19. In Proceedings of the Proceedings—2021 International Conference on Computing, Electronics and Communications Engineering, iCCECE 2021, Virtual. 16–17 August 2021; pp. 25–29.
44. Bag, S.; Aich, P.; Islam, M.A. Behavioral intention of “digital natives” toward adapting the online education system in higher education. *J. Appl. Res. High. Educ.* **2022**, *14*, 16–40. [[CrossRef](#)]
45. Ferhatoglu, M.F.; Kartal, A.; Ekici, U.; Gurkan, A. Evaluation of the Reliability, Utility, and Quality of the Information in Sleeve Gastrectomy Videos Shared on Open Access Video Sharing Platform YouTube. *Obes. Surg.* **2019**, *29*, 1477–1484. [[CrossRef](#)] [[PubMed](#)]
46. McKinley, J. Critical Argument and Writer Identity: Social Constructivism as a Theoretical Framework for EFL Academic Writing. *Crit. Inq. Lang. Stud.* **2015**, *12*, 184–207. [[CrossRef](#)]
47. Shearer, R.L.; Park, E. The theory of transactional distance. In *SpringerBriefs in Open and Distance Education*; Springer Briefs in Open and Distance Education: Cham, Switzerland, 2019; pp. 31–38.
48. Walther-Thomas, C.; Bryant, M.; Land, S. Planning for Effective Co-Teaching The Key to Successful Inclusion. *Remedial Spec. Educ.* **1996**, *17*, 255–264. [[CrossRef](#)]
49. Davis, F.D. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Q. Manag. Inf. Syst.* **1989**, *13*, 319–339. [[CrossRef](#)]
50. Venkatesh, V.; Bala, H. Technology acceptance model 3 and a research agenda on interventions. *Decis. Sci.* **2008**, *39*, 273–315. [[CrossRef](#)]
51. Fishbein, M.; Ajzen, I. Belief, Attitude, and Behaviour: An Introduction to Theory and Research. In *Belief, Attitude, and Behaviour: An Introduction to Theory and Research*; Philosophy and Rhetoric: Austin Austin, TX, USA, 1975; pp. 411–450. ISBN 0201020890.
52. Venkatesh, V.; Davis, F.D. Theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. *Manag. Sci.* **2000**, *46*, 186–204. [[CrossRef](#)]
53. Song, Y.; Kong, S.C. Investigating Students' Acceptance of a Statistics Learning Platform Using Technology Acceptance Model. *J. Educ. Comput. Res.* **2017**, *55*, 865–897. [[CrossRef](#)]
54. Huang, F.; Teo, T.; Zhou, M. Chinese students' intentions to use the Internet-based technology for learning. *Educ. Technol. Res. Dev.* **2020**, *68*, 575–591. [[CrossRef](#)]
55. Rejón-Guardia, F.; Polo-Peña, A.I.; Maraver-Tarifa, G. The acceptance of a personal learning environment based on Google apps: The role of subjective norms and social image. *J. Comput. High. Educ.* **2020**, *32*, 203–233. [[CrossRef](#)]
56. Bandura, A. Self-efficacy: Toward a unifying theory of behavioral change. *Adv. Behav. Res. Ther.* **1978**, *1*, 139–161. [[CrossRef](#)]
57. Panigrahi, R.; Srivastava, P.R.; Panigrahi, P.K. Effectiveness of e-learning: The mediating role of student engagement on perceived learning effectiveness. *Inf. Technol. People* **2021**, *34*, 1840–1862. [[CrossRef](#)]
58. Zimmerman, B.J. Self-Efficacy: An Essential Motive to Learn. *Contemp. Educ. Psychol.* **2000**, *25*, 82–91. [[CrossRef](#)]
59. Rafique, G.M.; Mahmood, K.; Warraich, N.F.; Rehman, S.U. Readiness for Online Learning during COVID-19 pandemic: A survey of Pakistani LIS students. *J. Acad. Librariansh.* **2021**, *47*, 102346. [[CrossRef](#)]
60. Al-Harbi, K.A.S. e-Learning in the Saudi tertiary education: Potential and challenges. *Appl. Comput. Inform.* **2011**, *9*, 31–46. [[CrossRef](#)]
61. Martínez-Nuñez, M.; Borrás-Gene, O.; Fidalgo-Blanco, A. Virtual learning communities in Google plus, implications, and sustainability in MOOCs. *J. Inf. Technol. Res.* **2016**, *9*, 18–36. [[CrossRef](#)]
62. Goodhue, D.L.; Thompson, R.L. Task-technology fit and individual performance. *MIS Q. Manag. Inf. Syst.* **1995**, *19*, 213–233. [[CrossRef](#)]
63. Goodhue, D.L. Understanding User Evaluations of Information Systems. *Manag. Sci.* **1995**, *41*, 1827–1844. [[CrossRef](#)]
64. Alyoussef, I.Y. E-learning acceptance: The role of task–technology fit as sustainability in higher education. *Sustainability* **2021**, *13*, 6450. [[CrossRef](#)]

65. Al-Samarraie, H.; Teng, B.K.; Alzahrani, A.I.; Alalwan, N. E-learning continuance satisfaction in higher education: A unified perspective from instructors and students. *Stud. High. Educ.* **2018**, *43*, 2003–2019. [[CrossRef](#)]
66. Al-Emran, M. Evaluating the Use of Smartwatches for Learning Purposes through the Integration of the Technology Acceptance Model and Task-Technology Fit. *Int. J. Hum. Comput. Interact.* **2021**, *37*, 1874–1882. [[CrossRef](#)]
67. Rai, R.S.; Selnes, F. Conceptualizing task-technology fit and the effect on adoption—A case study of a digital textbook service. *Inf. Manag.* **2019**, *56*, 103161. [[CrossRef](#)]
68. Navarro, M.M.; Prasetyo, Y.T.; Young, M.N.; Nadlifatin, R.; Redi, A.A.N.P. The perceived satisfaction in utilizing learning management systems among engineering students during the COVID-19 pandemic: Integrating task technology fit and extended technology acceptance model. *Sustainability* **2021**, *13*, 669. [[CrossRef](#)]
69. Setyawan, A.; Aznam, N.; Paidi; Citrawati, T. Kusdianto Effects of the Google meet assisted method of learning on building student knowledge and learning outcomes. *Univers. J. Educ. Res.* **2020**, *8*, 3924–3936. [[CrossRef](#)]
70. Ansari, J.A.N.; Khan, N.A. Exploring the role of social media in collaborative learning the new domain of learning. *Smart Learn. Environ.* **2020**, *7*, 9. [[CrossRef](#)]
71. DeLone, W.H.; McLean, E.R. The DeLone and McLean model of information systems success: A ten-year update. *J. Manag. Inf. Syst.* **2003**, *19*, 9–30.
72. Cho, V.; Cheng, T.C.E.; Lai, W.M.J. The role of perceived user-interface design in continued usage intention of self-paced e-learning tools. *Comput. Educ.* **2009**, *53*, 216–227. [[CrossRef](#)]
73. Al-Adwan, A.S.; Albelbisi, N.A.; Hujran, O.; Al-Rahmi, W.M.; Alkhalifah, A. Developing a holistic success model for sustainable e-learning: A structural equation modeling approach. *Sustainability* **2021**, *13*, 9453. [[CrossRef](#)]
74. Yllmaz, R. Knowledge sharing behaviors in e-learning community: Exploring the role of academic self-efficacy and sense of community. *Comput. Human Behav.* **2016**, *63*, 373–382. [[CrossRef](#)]
75. Van Der Heijden, H. User acceptance of hedonic information systems. *MIS Q. Manag. Inf. Syst.* **2004**, *28*, 695–704. [[CrossRef](#)]
76. Venkatesh, V. Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model. *Inf. Syst. Res.* **2000**, *11*, 342–365. [[CrossRef](#)]
77. Park, E.; Baek, S.; Ohm, J.; Chang, H.J. Determinants of player acceptance of mobile social network games: An application of extended technology acceptance model. *Telemat. Inform.* **2014**, *31*, 3–15. [[CrossRef](#)]
78. Jimenez, I.A.C.; Garcia, L.C.C.; Violante, M.G.; Marcolin, F.; Vezzetti, E. Commonly used external tam variables in e-learning, agriculture and virtual reality applications. *Futur. Internet* **2021**, *13*, 7. [[CrossRef](#)]
79. Al-Rahmi, A.M.; Shamsuddin, A.; Wahab, E.; Al-Rahmi, W.M.; Alismaiel, O.A.; Crawford, J. Social media usage and acceptance in higher education: A structural equation model. *Front. Educ.* **2022**, *7*, 964456. [[CrossRef](#)]
80. Venkatesh, V.; Thong, J.Y.L.; Xu, X. Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Q. Manag. Inf. Syst.* **2012**, *36*, 157–178. [[CrossRef](#)]
81. Khayati, S.; Zouaoui, S.K. Perceived Usefulness and Use of Information Technology: The Moderating Influences of the Dependence of a Subcontractor towards His Contractor. *J. Knowl. Manag. Econ. Inf. Technol.* **2013**, *3*, 68–77.
82. Ariff, M.S.M.; Yeow, S.; Zakuan, N.; Jusoh, A.; Bahari, A.Z. The Effects of Computer Self-Efficacy and Technology Acceptance Model on Behavioral Intention in Internet Banking Systems. *Procedia-Soc. Behav. Sci.* **2012**, *57*, 448–452. [[CrossRef](#)]
83. Al-Marouf, R.A.S.; Al-Emran, M. Students acceptance of google classroom: An exploratory study using PLS-SEM approach. *Int. J. Emerg. Technol. Learn.* **2018**, *13*, 112–123. [[CrossRef](#)]
84. Al-Rahmi, A.M.; Shamsuddin, A.; Wahab, E.; Al-Rahmi, W.M.; Alyoussef, I.Y.; Crawford, J. Social media use in higher education: Building a structural equation model for student satisfaction and performance. *Front. Public Health* **2022**, *10*, 1–15. [[CrossRef](#)]
85. Sabi, H.M.; Uzoka, F.M.E.; Mlay, S.V. Staff perception towards cloud computing adoption at universities in a developing country. *Educ. Inf. Technol.* **2018**, *23*, 1825–1848. [[CrossRef](#)]
86. Sayaf, A.M.; Alamri, M.M.; Alqahtani, M.A.; Al-Rahmi, W.M. Information and communications technology used in higher education: An empirical study on digital learning as sustainability. *Sustainability* **2021**, *13*, 7074. [[CrossRef](#)]
87. Dumford, A.D.; Miller, A.L. Online learning in higher education: Exploring advantages and disadvantages for engagement. *J. Comput. High. Educ.* **2018**, *30*, 452–465. [[CrossRef](#)]
88. Guo, Z.; Xiao, L.; Van Toorn, C.; Lai, Y.; Seo, C. Promoting online learners' continuance intention: An integrated flow framework. *Inf. Manag.* **2016**, *53*, 279–295. [[CrossRef](#)]
89. Salloum, S.A.; Qasim Mohammad Alhamad, A.; Al-Emran, M.; Abdel Monem, A.; Shaalan, K. Exploring students' acceptance of e-learning through the development of a comprehensive technology acceptance model. *IEEE Access* **2019**, *7*, 128445–128462. [[CrossRef](#)]
90. Alasmari, T.; Zhang, K. Mobile learning technology acceptance in Saudi Arabian higher education: An extended framework and A mixed-method study. *Educ. Inf. Technol.* **2019**, *24*, 2127–2144. [[CrossRef](#)]
91. Hussein, E.; Daoud, S.; Arabaiiah, H.; Badawi, R. Exploring undergraduate students' attitudes towards emergency online learning during COVID-19: A case from the UAE. *Child. Youth Serv. Rev.* **2020**, *119*, 105699. [[CrossRef](#)]
92. Rhema, A.; Miliszewska, I. Analysis of Student Attitudes towards E-learning: The Case of Engineering Students in Libya. *Issues Inf. Sci. Inf. Technol.* **2014**, *11*, 169–190. [[CrossRef](#)] [[PubMed](#)]
93. Kankanhalli, A.; Pee, L.G.; Tan, G.W.; Chhatwal, S. Interaction of individual and social antecedents of learning effectiveness: A study in the IT research context. *IEEE Trans. Eng. Manag.* **2012**, *59*, 115–128. [[CrossRef](#)]

94. Broadbent, J. Comparing online and blended learner's self-regulated learning strategies and academic performance. *Internet High. Educ.* **2017**, *33*, 24–32. [[CrossRef](#)]
95. Reyshav, I.; McHaney, R. The relationship between gender and mobile technology use in collaborative learning settings: An empirical investigation. *Comput. Educ.* **2017**, *113*, 61–74. [[CrossRef](#)]
96. Cavanaugh, J.K.; Jacquemin, S.J. A large sample comparison of grade based student learning outcomes in online vs. Face-to-Face courses. *J. Asynchronous Learn. Netw.* **2015**, *19*, n2. [[CrossRef](#)]
97. Pradana, M.; Amir, N.W. Measuring e-learning effectiveness at Indonesian private university. *Int. J. Environ. Sci. Educ.* **2016**, *11*, 11541–11554.
98. V.Rasiah, R.R. Transformative Higher Education Teaching and Learning: Using Social Media in a Team-based Learning Environment. *Procedia-Soc. Behav. Sci.* **2014**, *123*, 369–379. [[CrossRef](#)]
99. Alalwan, N.; Al-Rahmi, W.M.; Alfarraj, O.; Alzahrani, A.; Yahaya, N.; Al-Rahmi, A.M. Integrated three theories to develop a model of factors affecting students' academic performance in higher education. *IEEE Access* **2019**, *7*, 98725–98742. [[CrossRef](#)]
100. Kyei-Blankson, L.; Ntuli, E.; Donnelly, H. Establishing the Importance of Interaction and Presence to Student Learning in Online Environments. *World J. Educ. Res.* **2016**, *3*, 48–65. [[CrossRef](#)]
101. Affouneh, S.; Salha, S.; Khlaif, Z.N. Designing Quality E-Learning Environments for Emergency Online Teaching in Coronavirus Crisis. *Interdiscip. J. Virtual Learn. Med. Sci.* **2020**, *11*, 135–137.
102. Hair, J.F.; Risher, J.J.; Sarstedt, M.; Ringle, C.M. When to use and how to report the results of PLS-SEM. *Eur. Bus. Rev.* **2019**, *31*, 2–24. [[CrossRef](#)]
103. Nadlifatin, R.; Ardiansyahmiraja, B.; Persada, S.F. The measurement of university students' intention to use blended learning system through technology acceptance model (tam) and theory of planned behavior (TPB) at developed and developing regions: Lessons learned from Taiwan and Indonesia. *Int. J. Emerg. Technol. Learn.* **2020**, *15*, 219–230. [[CrossRef](#)]
104. Alamri, M.M.; Al-Rahmi, W.M.; Yahaya, N.; Al-Rahmi, A.M.; Abualrejal, H.; Zeki, A.M.; Al-Maatouk, Q. Towards adaptive e-learning among university students: By applying technology acceptance model (TAM). *Int. J. Eng. Adv. Technol.* **2019**, *8*, 270–276. [[CrossRef](#)]
105. Karimi, S. Do learners' characteristics matter? An exploration of mobile-learning adoption in self-directed learning. *Comput. Human Behav.* **2016**, *63*, 769–776. [[CrossRef](#)]
106. Alshaikh, K.; Maasher, S.; Bayazed, A.; Saleem, F.; Badri, S.; Fakieh, B. Impact of COVID-19 on the educational process in Saudi Arabia: A technology–organization–environment framework. *Sustainability* **2021**, *13*, 7103. [[CrossRef](#)]
107. Al-Rahmi, W.M.; Yahaya, N.; Aldraiweesh, A.A.; Alamri, M.M.; Aljarboa, N.A.; Alturki, U.; Aljeraiwi, A.A. Integrating Technology Acceptance Model with Innovation Diffusion Theory: An Empirical Investigation on Students' Intention to Use E-Learning Systems. *IEEE Access* **2019**, *7*, 26797–26809. [[CrossRef](#)]
108. Al Kurdi, B.; Alshurideh, M.; Nuseir, M.; Aburayya, A.; Salloum, S.A. The Effects of Subjective Norm on the Intention to Use Social Media Networks: An Exploratory Study Using PLS-SEM and Machine Learning Approach. In *Advances in Intelligent Systems and Computing*; Springer Science and Business Media Deutschland GmbH: Berlin, Germany, 2021; Volume 1339, pp. 581–592.
109. Ching-Ter, C.; Hajiyev, J.; Su, C.R. Examining the students' behavioral intention to use e-learning in Azerbaijan? The General Extended Technology Acceptance Model for E-learning approach. *Comput. Educ.* **2017**, *111*, 128–143. [[CrossRef](#)]
110. Kim, R.; Song, H.-D. Examining the Influence of Teaching Presence and Task-Technology Fit on Continuance Intention to Use MOOCs. *Asia-Pac. Educ. Res.* **2021**, *31*, 395–408. [[CrossRef](#)]
111. Denan, Z.; Munir, Z.A.; Razak, R.A.; Kamaruddin, K.; Sundram, V.P.K. Adoption of technology on e-learning effectiveness. *Bull. Electr. Eng. Informatics* **2020**, *9*, 1121–1126. [[CrossRef](#)]